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Stealthy Health Sensing to Objectively Characterize Motor Movement Disorders

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Abstract

Hyperkinetic movement disorders affect people in a wide range of ages, from children with autism motor stereotypies to the elderly with Parkinsonian tremor. Unwanted normal and or abnormal movement of the arms significantly affects the quality of life for both young and old. Physicians who manage chronic neurological movement diseases (e.g., Parkinsons) tend to make many decisions based on subjective information without access to objective data that can be difficult to routinely obtain. Assessment information is obtained today by tests characterized as pencil-and-paper tests and from observations that classify behavior of motor response or reaction time. Other assessment approaches rely on technologies such as accelerometers, electromyography, and, more recently, sensors built into smartphones and tablets to obtain test results.

In the market today, *all* smartphone centric solutions still lack both objectivity in the measured data and automatic continuous long-term analysis. In this article, we propose a new smartphone solution that uses ***stealthy health sensing*** to more objectively characterize neurological movement disorders using built-in sensors. We evaluate the mobile app by characterizing and monitoring tremor, one of the most common neurological movement disorders. Its objective characterization is important for etiologic consideration and *personalized* treatment.

Keywords: mobile computing, accelerometer, stealth health sensing, personalized health, tremor, movement disorders

1. Introduction

One of the symptoms characteristically exhibited in Parkinson's disease (PD) is upper and lower limb tremor. One million people in the U.S. and seven to ten million people worldwide [1, 2] suffer from PD. In 2006 to 2008 new diagnoses rose to about 50,000 per year. Today the rate centers around 60,000 new diagnoses each year [1]. Given the numbers of PD cases, an increasingly aging population (not only in the U.S., but elsewhere as well), and the numbers of young onset PD cases rising (21-40 year olds receiving a diagnosis of PD) the need to provide more effective and ***personalized*** management of the disease has

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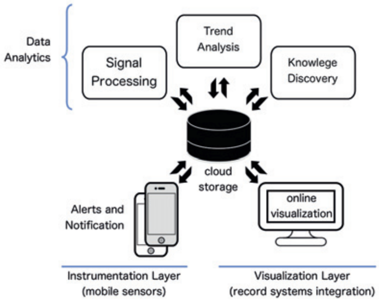
never been more important. One of the areas where focus has been directed to is how movement disorders contribute to depression and lower quality-of-life (QOL) for people diagnosed with PD. Other movement disorders of the nervous system that causes involuntary rhythmic shaking include essential tremor (ET), focal dystonia, and multiple system atrophy to name a few. Tremor is one of the most common movement disorders generally characterized by involuntary, rhythmic, oscillating movement of a body part (often the arms and hands) occurring in isolation or as part of a clinical syndrome [3, 4, 5]. For many, tremor is a debilitating symptom severely affecting QOL. Slowing the progression of the disease and minimizing negative impact of the symptoms have considerable economic implications [6] motivating the search for new ways to address the problem.

Physicians who manage chronic disease such as PD tend to make decisions based on subjective information without access to sufficient, objective, and quantitative measures of motor symptoms. Standard clinical assessment of PD motor symptoms uses a comprehensive scale, the Unified Parkinsons Disease Rating Scale (UPDRS), which incorporates multiple elements that contribute to motor impairment or disability [7, 8]. The problem with this approach is that it is difficult to obtain objective measures of the motor symptoms. Furthermore, infrequent visits to the doctor exacerbate the problem of incomplete information available to physicians leaving them to make decisions with both, inaccurate and incomplete data. Lack of sufficient information translates to less precise, one-size fits all, and impersonal treatment plans for management of the disease.

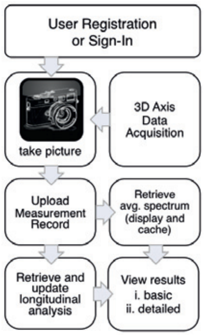
In this article, we propose a novel method for characterizing neurological motor movement disorders. This method offers more objectivity compared to current solutions. Furthermore, it also offers more quantitative accuracy, is less intrusive, and none invasive. Aiming to obtain better accuracy in the measurements will allow us to capture small symptom changes normally not seen in routine visits to the neurologist. Our approach relies fully on the use of smartphones' built-in accelerometer. Objective characterization of tremor yields more valuable information on which physicians can rely to develop personalized treatment and improve long-term management of chronic diseases. The problem with current approaches is that a subject must make time to perform a test. The subject is always conscious of the fact that he or she is performing a test no matter how simple it might be. Our approach is less intrusive, because our method captures motor information while subjects use the smartphone for its core functionality (e.g., composing a text message, browsing a web-page, or taking a picture).

PD typically affects the elderly, a population more willing to participate in at-home patient monitoring when tasks are simple and uncomplicated. Our approach makes it both simple and easy to sense the desired information for individuals that use mobile phones on a daily basis. This work introduces TremVibe [9], a smartphone app that is easy to use, because data-acquisition takes place using the concept of ***stealthy health sensing***. By contrast, other electronic instruments used to assess tremor in a physician's office setting tend to require wearing wireless sensors on various parts of the arms and legs. Furthermore, other methods use electromyography (EMG) instruments, which require the use of probes to be attached to the skin. While probes are perfectly safe, this method still makes some subjects uncomfortable. TremVibe simply requires subjects to use their smartphone in routine fashion as mentioned above. Providing less intrusive and less invasive methods to collect the true signature of tremor will translate into more personalized assessment, more objective measurements, and more detailed information on which physicians can rely on to make treatment decisions. Personalized and improved chronic disease management will yield a better quality of life for the many suffering from tremor caused by PD or essential tremor (ET).

Stealthy health sensing is a novel approach that yields more objective experimental data and encourages sustained participation in patients' own health tracking. TremVibe accomplishes the latter through its non-intrusive data acquisition at-home monitoring approach. TremVibe's system level architecture and a flow diagram of how data is acquired is shown in Figure 1. The system (Fig. 1a) consists of four main components: the instrumentation layer (i.e., the data acquisition), data analytics, data visualization, and cloud (or remote) storage. The flow diagram showing how the app works (Fig. 1b) for collecting acceleration data when the camera option is used. In Section 2 we make the case for stealth health sensing, discuss the strengths, and potential downsides of this new approach. In Section 3 we describe in detail the methods for evaluating stealthy sensing, where this approach can be applied to longitudinal monitoring of tremor, Parkinsonian or others. We conclude by presenting results and summarize this work together with a list of



(a) System Overview



(b) Functional Flow Diagram

Fig. 1: TremVibe System and app overviews: ***(a)*** system (cloud server) level overview and ***(b)*** camera app functional flow overview

open challenges.

1.1. Related Work

Smartphones and tablets are increasingly being used for health evaluations and testing, including the assessment of movement disorders. For example, Joundi et al. used iSeismo, an app available for iPhone and Android devices originally aimed at earthquake sensing, to test patients with various types of tremor [10]. This group carried out a set of experiments where the smartphone and the EMG probes were attached to a hand and arm muscles respectively. They took measurements using the EMG instrument while the users held the iPhone with the iSeismo app running. They measured tremor's fundamental frequency on iSeismo and correlated it to measurements on the EMG instrument. This approach validates iSeismo as a tool that can be used to find the fundamental frequency of a subject's tremor, but the app was developed by others so it is not flexible and is limited in features. The raw three-dimensional (3D) acceleration information cannot be extracted and use of this app is limited to capturing a screenshot of the plotted results.

Kostikis et al. developed a smartphone web-app called TremorSense [11] . It detects and quantifies hand tremor using built-in accelerometer and gyroscope. Their approach was to obtain acceleration and rotation information, because observations of patients with movement disorders show that tremor has a rotational component. The downside of this approach is that the app is a web-app and the use of JavaScript limited fine-tuned control of the sampling frequency. The problem is that with too low of a sampling frequency, some tremor information may not be properly captured.

Lemoyne et al. developed a tremor glove where the smartphone is attached. This app acquires accelerometer readings for 10 seconds and is repeated 10 times [12]. The downsides of their methodology range from the test being too long and motor adaptation may begin to contribute to the results. Any contribution from motor adaptation can corrupt true tremor signature, which affects objectivity. In addition, the patients are aware that they are taking a test (which adds to the problem of objectivity in the measured data), the patient sample size of one is too small, and they do not account or correct for any signs of motor adaptation: learning to control tremor by sensory prediction [13].

iTrem is an app developed by Delano and colleagues that collects arm-hand tremor by using a quick test or by playing a game on the smartphone [14]. They have been able to establish collaborations with various hospitals and plan to obtain FDA approval. The downside of their approach is that the test is not very objective even if they use gaming techniques. Subjects are still aware of the test and could be manipulated.

The works listed above by these teams have the following strengths respectively, *i*) repurposing a standard, but mature app, *ii*) a multi-platform web-app, *iii*) consistency, and *iv*) a mature app and collaboration with a number health institutions to thoroughly verify its functionality. However, they are all vulnerable to the white-coat effect and do not yield more exacting measures of motor movement signature as those obtained by EMG. In contrast, the proposed stealthy health sensing approach can provide more objective measurements and is not subject to those other factors mentioned before. Another significant difference is that our approach allows for multiple opportunities to sample tremor rather than only during infrequent visits to the doctor. The next section makes the case for stealthy health sensing in application areas where the benefit is significant.

2. TremVibe and the Stealthy Health Sensing Concept

2.1. Background

Stealthy health sensing captures discrete streams of data (acceleration) as the patient utilizes the smartphone in a natural or typical way, that is making or receiving a phone call, browsing the Internet, or taking a picture. Acquiring movement information is done in an unobtrusive and natural way and not as at test. A group at University of Arizona is one of the first to coin the term *stealth health* using mobile phones to promote physical activity and increase nutrition knowledge among the youth [15]. Many activity detection and activity recognition health apps, which rely on inference protocols, acquire movement and motion data while users go about their daily routine [16, 17]. Other apps use a stealth approach to rely on motion taps (i.e., acceleration) on a smartphone screen to infer key presses, for a summary of related work see [18, 19, 20]. Stealth health sensing for tremor characterization and long-term monitoring fully integrated with cloud computing services that analyze tremor data in real-time and output feedback information to both test subjects and physicians is a novel approach and a first of its kind.

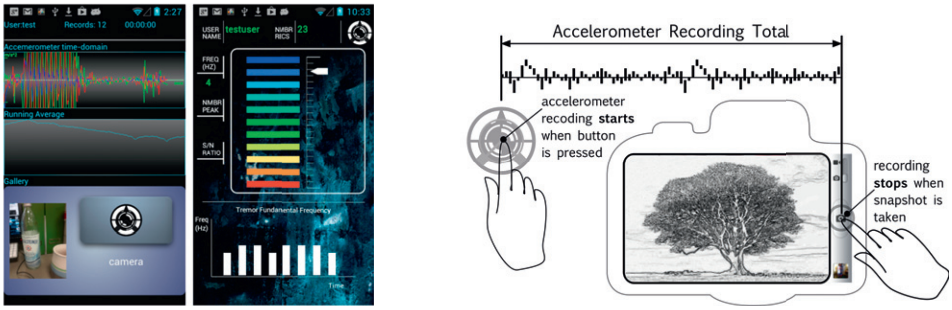
This approach offers various potential benefits, but leading the list is nonintrusive data acquisition. Obtaining motor movement information while subjects perform normal operations on their smartphone (reading a message, email, browsing, or taking a picture) ensures that recordings are not impacted by the awareness that a subject is performing a test. While the proposed stealthy health sensing can be applied to various health conditions, this article focuses on PD tremor. The accelerometer in smartphones is enabled to acquire triaxial acceleration information, which is processed to identify signs of a fundamental frequency, a feature often related to rhythmic motor movement.

Home monitoring technology has increased in recent years. Its acceptance, by both the patient and the physician, is critical to increasing participation in one's own healthcare and potentially reducing costs. Leveraging smartphone technology and using stealthy health sensing as new approach for long-term data gathering has great potential to address these problems in a significant way.

Potential downsides to this approach are dominated by assumptions that solely the patient will use the app. In controlled settings, i.e., a physician's office or medical clinical, a guarantee that the experimental data is collected from the subjects in question is more certain. However, in an at-home or remote setting, where the subjects in question are not monitored, the guarantee that the subject is the one handling the smartphone is not as robust. Other downsides center on perceived notions of what else is the app sensing or recording about the subjects' typical daily activities. Apprehension may build up as a result, thus discouraging participation.

2.2. Mobile Technology

Mobile technology, specifically smartphones, has exhibited great potential in making health services accessible for **patient home monitoring** and **telemedicine** applications. This work leverages sensor-rich smartphones with built-in inertial motion sensors such as accelerometers and gyroscopes to deliver patient home monitoring. Mobile sensors allow for automatic discrete sampling of neurological tremor between physician visits. Smartphones are equipped with several sensors (e.g., microphones, camera, light, and proximity sensors) including inertial measurement units such as digital compasses, magnetometers, triaxial gyroscopes, and accelerometers. Accelerometers measure acceleration forces exerted on the mobile device (on which they are mounted). We collect these measurements and perform digital signal processing, frequency, and time-series analysis.



(a) TremView Admin and User Views (b) Data Acquisition: Sensing During Picture Taking

Fig. 2: TremVibe Screenshots and the Tremor Sensing Phase

2.3. TremVibe: The Mobile App

TremVibe is a photo app developed for the Android operating system. Designed as a native app, the app lets registered users take photos and in background-mode the accelerometer sensor is activated to record vibration and acceleration for the duration of snapshot. After a photo is taken the 3D acceleration data is uploaded, asynchronously from user-interface thread to a remote server. The app features, as currently designed, features a view with plots of the time-domain sensor data for all three axes (x, y, and z). Figure 2a shows the admin and the user views. The admin's view is intended for patients who want to see details of each test, but especially for researchers and physicians. The Admin view offers time-domain plots of 3D acceleration and averaged frequency response (frequency spectrum plot) of the user's previous records. The user's view offers basic statistics and simple graphs showing trends and progress over time. A bar-graph shows the longitudinal fundamental frequency if there are signs of any tremor or vibration in the acquired records. A variant of this app could implement only acceleration sensing as a background service that can be triggered by specific events (e.g., incoming or outgoing calls or when launching the browser) to completely remove awareness of testing by the patient.

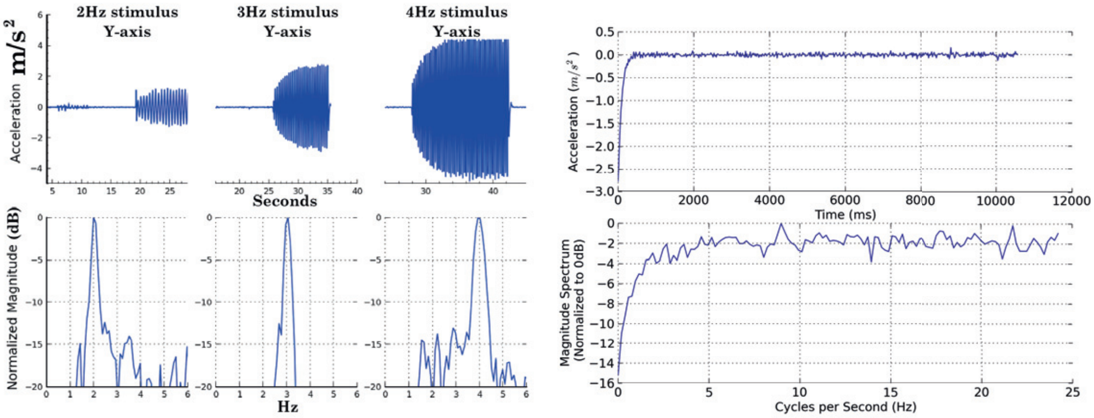
The average amplitude spectrum signal is fetched by the app each time users take a photo and upload their recording. A copy of these data is stored on the device as part of the mechanism to deal with temporary loss of network access. In other words, if users lack network access, the amplitude spectrum displayed is the last computed. A flag is set to asynchronously fetch the most recent amplitude spectrum when a later time.

3. Methods

A key feature is the ability to obtain acceleration measurements directly from the smartphone and upload them to a remote server. The 3D acceleration information is obtained from built-in accelerometer while the subject uses the device in three different modes. Data acquisition is triggered when the subject makes or receives a phone call, launches a browser, and snaps a photo (see Figure 2b). Movement information is acquired until one of these actions comes to a stop (i.e., when the phone call ends, when the subject ends or switches out of the browser app, or when the photo is snapped and accepted). The application is configured to store triaxial (X, Y, and Z-axis) accelerometer sensor data into arrays with the time-stamp, also stored in an array, to compute the actual sampling frequency. The data in these arrays are sent and stored in a remote database (MySQL).

TremVibe was evaluated using the following computing platforms for the mobile app and the back-end cloud system respectively: Google Nexus S with android Version 4.1.1 (with KR3DM 3-axis accelerometer part) and a desktop system with the following characteristics: Dual Core Intel(R) Pentium(R) D CPU 3GHz with 2GB of memory and 160GB of storage.

Validating the accuracy of the accelerometer sensor readings was performed using physical stimulus using controlled frequency forces using a portable bench-scale shake table power by a three-phase brushless



(a) (b)

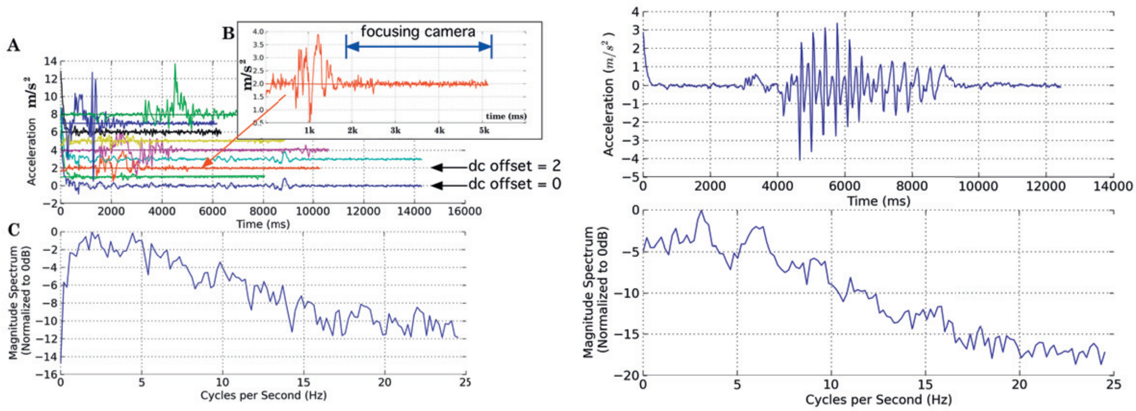
Fig. 3: **(a)** Accelerometer accuracy verification: The smartphone is placed on a shaker table (physical frequency generator: Quanser Shake Table II) and a controlled stimulus shakes the table at a selected frequency. **(b)** Zero g XYZ Acceleration: With the Smartphone in a Stationary Position

motor. This table provides single-axis stimulus at a controlled frequency range between 0 and 20 Hertz (Quanser Shake Table II).

4. Results

4.1. Evaluations

Validating TremVibe consisted of performing the following evaluations: i) accuracy verification, ii) correcting for Earth's gravity, and iii) simulating tremor symptoms (simulated experimental measurements). Determining acceleration accuracy and correcting for Earth's gravity corresponds to calibration of the system. The acceleration accuracy and correction measurements are shown respectively in Figures 3a and 3b.



(a) (b)

Fig. 4: **(a)** Acceleration from normal control subjects: $N = 1$, $n = 10$, where N is the number of subjects and n is the number of recordings per subject over time, **(b)** *Simulated* Tremor: using the smartphone

After validating the test platform (smartphone and Android app) that it can accurately sense a controlled stimulus, data were collected from healthy individuals to build a control baseline. Figure 4a shows the Xaxis acceleration for 10 camera snapshots and plotted with an offset of 1 relative to each recordig (Fig. **4a-A**). The time duration of the snapshot varies, but there is a characteristic in healthy individuals highlighted in (Fig. **4a-B**). Towards the end of the data collection subjects focus and maintain the smartphone relatively steady at the time of taking the snapshot. Finally, in (Fig. **4a-C**) we sliced the time-series sequence into 256-point sections and computed the FFT and averaged the resulting frequency response. Shown here is the result of using the entire number of points in this recording. We can further choose to ignore the first 20% of samples to show only frequency response of the steady part of each recording to obtain and evaluate on the information where the user is consciously and actively trying to maintain a steady pulse on the smartphone to take a picture.

4.2. Analysis of the Results

Figure 3a shows acceleration force exerted on the smartphone at controlled frequencies while the app is running and simulating taking a picture. We can verify that the smartphone platform can accurately capture the exerted forces at frequencies two, three, and four Hertz (Hz). The time-domain acceleration amplitudes are plotted on the top of the figure. The corresponding frequency spectrum shows that the frequency of the periodic acceleration centers on two, three, and four Hz.

Compensating for the Earth's gravity is shown in Figure 3b. Here repeated acceleration measurements in the X, Y, and Z orientations are captured and then averaged (n=10, in each direction or orientation). The plot shows the acceleration stays around 0g. The corresponding frequency domain exhibits a flat magnitude spectrum.

Results of control and simulated tests, in Figure 4a, show 3D (X, Y, and Z-axis) time-series acceleration data for a selected control (N) subject. Data is collected over time (n is 10). While the subject took a picture the triaxial acceleration was acquired and stored remotely. A typical control subject does not yield significant rhythmic oscillation or tremor while taking a photo as the figure shows.

On the other hand, simulating arm and hand tremor (rhythmic vibration) while taking a photo can show signs of a fundamental frequency emerging. Here, a subject shakes lightly while taking a picture. Figure 4b shows both the time-domain averaged triaxial acceleration and the resulting Fourier transform magnitude spectrum. The spectrum is analyzed for features (e.g., fundamental frequency, number of peaks, peak amplitude, root mean square, etc.) that are used to characterize the acceleration signatures of PD tremor. Features from individual recordings are compared to both, features from the running average and to features from a baseline of healthy subjects (normal controls) to obtain a set of weights (or values) that physicians can interpret. Physicians can use the new information to personalize a patient's treatment plan. The logical next set of step is to partner with a movement disorders medical facility to deploy the app in a controlled clinical setting or systematically enlist research volunteers diagnosed with neurological tremor to use the tracking TremVibe offers and share the results with their physicians or healthcare provider.

5. Conclusion

We have demonstrated that using sensor-rich smartphones we can obtain reliable triaxial acceleration information to determine the characteristics of motion forces of upper limb tremor. Use of smartphones in a traditional everyday fashion to monitor and assess motor movement in stealth-mode can yields reliable and more objective characterization of motor movement signature. The ***stealthy health sensing*** approach offers a new way to monitor certain vital signs in people with chronic disease and offers a potential for increased participation in one's own health monitoring. This can be accomplished through the use of simple and non-intrusive technology. The information generated using TremVibe will lead to a more personalized and more informed treatment of chronic disease. Other areas where stealth health sensing could be complementary fit include activity recognition (AR) using smartphones. The work by Albert et al. in [16] used mobile phones to comprehensively assess activity recognition in Parkinson's patients. Their study shows that tremor symptoms can adversely affect activity recognition, thus making it challenging to use mobile phone devices on patient populations with motor disabilities. How much AR is adversely affected could be correlated to temporal severity of PD tremor.

Future work will initially center on evaluating the stealthy sensing concept and TremVibe on patient populations with different stages of PD and related neurological movement disorders. In additional to the desktop system described in the methods section, we are experimenting with a cloud system that offers a mechanism to scale up as the numbers of users increases (EC2 from Amazon AWS [9]). Further, we will look at additional application areas of stealth sensing, e.g., patients affected by neurological disorders that cause limb tremor and where having access to patient response to treatment information on a more regular basis helps deliver a more personalized level of care.

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